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# CoenoFire: Monitoring Performance Indicators of Firefighters in Real-world Missions using Smartphones

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## ABSTRACT

Firefighting is a dangerous task and many research projects have aimed at supporting firefighters during missions by developing new and often costly equipment. In contrast to previous approaches, we use the smartphone to monitor firefighters during real-world missions in order to provide objective data that can be used in post-incident briefings and trainings. In this paper, we present CoenoFire, a smartphone based sensing system aimed at monitoring temporal and behavioral performance indicators of firefighting missions. We validate the performance metrics showing that they can indicate why certain teams performed faster than others in a training scenario conducted by 16 firefighting teams. Furthermore, we deployed CoenoFire over a period of six weeks in a professional fire brigade. In total, 71 firefighters participated in our study and the collected data includes 76 real-world missions totaling to over 148 hours of mission data. Additionally, we visualize real-world mission data and show how mission feedback is supported by the data.

### Author Keywords

smartphone sensing; human behavior observation; team performance; real-world deployment; firefighting

### ACM Classification Keywords

H.1.2 User/Machine Systems; H.5.3 Group and Organization Interfaces; J.4 Social and Behavioral Sciences

### General Terms

Experimentation, Human Factors, Algorithms, Performance.

## INTRODUCTION

Firefighting is a dangerous and potentially life threatening task. Firefighters work in unfamiliar situations under a high degree of uncertainty and time is critical [9]. To overcome these challenges team work is of utmost importance. High team performance of firefighters is crucial for saving lives and protecting property and environment.

During missions each firefighter fulfills a specific function and relies on his peers. These individual functions and their related activities have to be coordinated within the team. As a result, effective coordination is vital for firefighting, which is in line with the general finding that team coordination is an important correlate for performance [17]. As coordination and performance unfold in time, continuous monitoring is important to investigate these processes in detail.

In our view, ubiquitous computing can help to continuously monitor performance indicators of firefighters during real-world missions and to assist incident commanders as well as training instructors with objective data during post-incident feedback and training. As most firefighters of our study already carry their mobile phone with them, even during missions, the smart phone can serve as a rich sensor platform to unobtrusively monitor firefighters.

Our goal is a system that can be used to capture performance indicators of firefighters in training scenarios as well as real-world missions. In close collaboration with a professional fire brigade, we defined a set of performance metrics that can be extracted from the smartphone data. Furthermore, we visualize the sensor data to show how missions evolve over time to automatically create a high level log book with important events of a mission. In particular, our contributions are:

1. We describe how sensor data over a period of several weeks can be collected in a hazardous, real-world work environment. We analyse requirements, detail our implementation of our sensing system CoenoFire and present lessons learned.

2. Considering speech and movement activity as proxy of explicit team coordination and team effort, we analyse the relationship to the critical performance measure of completion time in a realistic training scenario.

3. We show how real life missions evolve over time and demonstrate how mission phases and important firefighting events such as time of arrival and first troop in house can be automatically logged.


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## RELATED WORK

In this section, we detail related work on the two main aspects of the paper. First, we summarize technical projects which aimed at supporting firefighters. Second, we review current smartphone sensing applications.

### Supporting Firefighters

Previous research projects which aimed to support firefighters focused on three aspects: monitoring of firefighters' health during missions, monitoring of the environment of firefigthers for toxic gases and high temperatures and providing navigational support.

The European Union funded several research projects which aimed at supporting and increasing work safety of firefighters. The ProeTEX project [3] developed a system including a smart textile to monitor the physiological status of the firefighter. Within the emergency response part of the wearIT@work project [5], the LifeNet, a beacon based relative positioning system, was proposed to support tactical navigation under poor visibility. To increase acceptance by the firefighters the LifeNet approach was adapted in the ProFiTex project [4] to better integrate with current practices of firefighting brigades and resulted in a Smart Lifeline to which firefighters are connected and data can be transmitted out of the building to the incident commander. The NIST Smart Firefighting Project [2] combines research in smart building technology, smart firefighter equipment and robotics. Like in previous projects the aim is to provide real-time information on firefighter location, firefighter vital signs, and environmental conditions to the firefighter, incident commander, and other firefighters. The Fire Information and Rescue Equipment project [1] at UC Berkeley combined wireless sensor networks and small head-mounted displays to support firefighters. In [24] a fixed wireless sensor network enables the communication between emergency responders and the incident commander. Multiple prototypes of localisation and navigation systems have been developed to support firefighters. In a recent review [15] the benefits and drawbacks of preinstalled location systems, wireless sensor systems and inertial tracking systems for emergency responders were compared.

All of the above projects focused on supporting firefighters on-site. Although system prototypes were tested in simulated scenarios none of these project ideas were used in real-world missions. Our approach puts the focus on real-world deployment and usage during actual incidents. In this paper, we do not put our primary focus on supporting firefighters during missions when time is critical but rather on documenting mission operations in order to support post mission feedback and further trainings. However, CoenoFire offers real-time feedback of performance indicators and can be used to monitor ongoing missions, provided that the area of operation is covered by the mobile network.

### Smartphone Sensing

As we use the smartphone as our sensing platform, we review existing smartphone sensing applications targeted at monitoring an individual or a group of persons.

The smartphone, with more and more built-in sensors, has evolved into a ubiquitous sensing platform and recent research has shown how user context and behavior can be inferred. Studies dealt with inference and detection of important places [8], detection of daily routines [12], as well as the detection of users emotions [22], experienced stress [18] and personality [7]. Automatic assessment of well-being with the smartphone was explored in [21]. On a population level, communities have been first identified from Bluetooth proximity networks by Eagle et. al. [11], and only recently topic models were used to discover human interactions from proximity networks [10].

Instead of using the smartphone, Olguin et. al. used sociometric badges to collect behavioral data of 67 nurses in the Post Anesthesia Care Unit of a hospital [20]. The results showed a positive relationship of group body motion energy and speaking time with group productivity.

In previous work [14], we adopted the idea to use motion and speech activity to monitor teams. Our feasibility study showed that speech and motion activity are promising performance indicators in firefighting teams. However, to the best of our knowledge, no previous study has attempted the monitoring of professional firefighters during real-world missions using only the smartphone.

## PERFORMANCE INDICATORS

The performance of a firefighting squad depends on a set of criteria and there exist no single measure of performance. During missions, firefighters have to keep in mind several objectives, but obviously own safety stands above all, followed by rescuing other lives and protecting property.

Firefighting squads can be considered as action teams that are characterized by expert members conducting complex, time-limited tasks in challenging environments [23]. As delays can be disastrous, time is a critical factor in evaluating the performance of firefighters [9]. In this regard, two temporal aspects can be distinguished: speed and timing. Action teams need to complete their tasks quickly. Moreover, the right timing of team activities (when to do what) is crucial for success. Phase models of team processes [19] highlight this second aspect of temporality. For example, planning activities should be finished prior to task execution.

To assess the speed aspect of time related team performance, we propose to use *timing measures* of important events during missions. This includes the time of arrival on-site, as well as the time of a first troop entering a building. We will therefore aim to detect these events automatically from the smartphone sensor data.

In addition, we extract the following behavioral performance metrics from the sensor data. We measure *team effort* as the amount, intensity and variability of physical activity, reasoning that higher team effort is expressed in more physical activity. Furthermore, we access *team coordination* as the amount of speech activity. The idea behind is that the more firefighters have to explicitly co-ordinate their actions, the more they have to communicate.

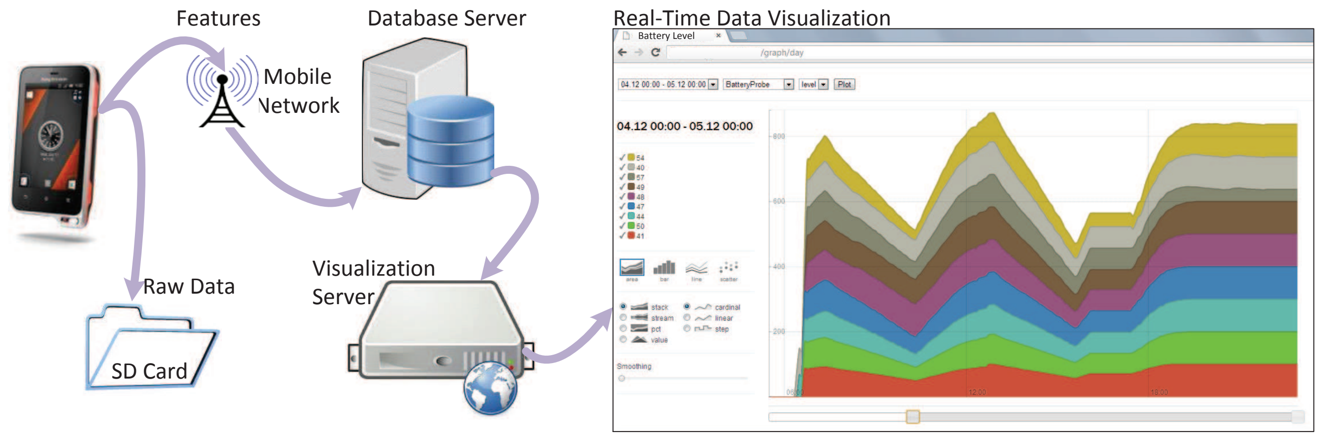


**Figure 1. CoenoFire: Smartphone based data collection framework. Raw smartphone sensor data is saved to the SD-Card and features are transmitted via the mobile network to enable real-time monitoring of performance metrics and system status, e.g. battery level.**

## COENOFIRE SYSTEM

In the following, we detail our approach to monitor performance indicators of firefighters and describe CoenoFire, our mobile sensing system to monitor firefighters on-duty.

### Requirements on Monitoring System

For a successful data collection in a real working environment it is of utmost importance not to infer with day to day operations. In the case of monitoring firefighters this is in particular true as time is critical and firefighters will not accept any delays when they leave the station for a mission. At the same time, the system should run reliably and be always ready to record data. Consequently, in order to monitor firefighting missions 24/7, one has to find a practical solution to charge the smartphones reliably without much user effort and to start and stop the data recording automatically.

To ease administration and to be able to respond to possible data collection problems, for example when firefighters forget to charge the smartphone after returning from a mission, the system should further support some real-time feedback on it's current state, such as the battery level of each smartphone.

Additional information about an incident may be obtained during a post mission questionnaire. However, the number of questions asked to each firefighter should be kept to a minimum, because time consuming questionnaires will result in missing data as firefighters have more important tasks than filling out questionnaires.

### Data Collection Framework

Our data collection framework CoenoFire consists of two parts, the smartphone data collector as the sensing front-end and a database and visualisation server in the backend. The overall data flow is illustrated in Figure 1.

For data collection, we used the Sony Xperia Active Smartphone which was designed for active people. It features a dust and water-resistant case, a 3-inch capacitive touchscreen and a built-in ANT radio[1] to communicate with fitness devices such as heart-belts. We choose the phone for the data collection because of it's small form factor and it's robust design.

#### *Front-End: Smartphone Data Collector*

Based on the funf-open-sensing-framework [6], we designed an Android app to sample the phone's built-in sensors. For robustness reasons, each sensor was sampled in a separate background service and we extended the framework to save the raw sensor data to the memory card.

We recorded the data from the following built-in sensors: acceleration and orientation sensors were used to measure body movement, the barometer measured atmospheric pressure and was used to infer whether firefighters were on different floor or ground levels, the microphone captured raw audio data which was analyzed for speech, GPS location fixes were used to record incident location and driving speed and ANT-based radio messages were send and received to find out which firefighter was in proximity to another one.

As we aim to monitor firefighting teams, the timestamps of all devices have to be synchronized. We used the network time protocol (NTP) to measure the offset between system time and a common reference time each 5 min. With this approach, we were able to achieve a time synchronisation across devices with a maximum time difference of 500 ms.

In order to monitor the status of the smart phone data collector, we configured the framework to upload a subset of calculated features, such as the battery level and a sliding mean value of the acceleration signal to a central server. The upload period was set to five minutes.

We installed our app as default homescreen and blocked all soft buttons of the smartphone to prevent the firefighters to play around with any smartphone settings. In this way, our app was always visible and the use of the smartphone was restricted to our data collection.

[1] `http://www.thisisant.com`

*Back-End: Database and Visualisation*

On the server side, we run one webserver to receive the data from the smartphones via http-post requests. Upon each request, the data was extracted and stored it in a central database. A second webserver provided a web-based user interface offering to monitor the system in real-time. A screen shot of the web interface showing the battery status of the devices is presented in the right of Figure 1. The interface also allows to visualize real time data of the firefighters movement and speech activity. For the implementation, we used Tornado[2] as our webserver and choose MongoDB[3] as our database. For data visualisation, we used the javascript libraries d3.js[4] and ricksaw.js[5].

### Detection of Mission Phases

Based on GPS location fixes, we segment each mission into three different phases. The *approach* phase is the first phase of each mission and starts when the fire trucks leave the station. In the second phase the firefighters are *on-site* and in the third phase the mission is completed and the firefighters *return* to the station. To detect the phases, the average location of all firefighters was aggregated for each second of the mission operation, by taking the mean of all GPS fixes recorded within one second. Based on the squads location, we then calculated the distance to the fire station and the driving speed and applied a moving average filter of $5\,\mathrm{s}$ to smooth both measures. We defined the *on-site* phase to be the longest time segment in which the distance to the fire station was constant and greater than $200\,\mathrm{m}$. The start of the *approach* phase was defined to be the first second in which the distance to the firestation was at least $50\,\mathrm{m}$ and the squads movement speed was higher than $20\,\mathrm{km\,h^{-1}}$. The *return* phase ended as soon as the distance to the fire station was smaller $50\,\mathrm{m}$ and the squads movement speed was less than $20\,\mathrm{km\,h^{-1}}$.

### Detection of Group Proximity

Contrary to previous works which have relied on Bluetooth scans to detect proximity between people [11, 10], we use the low-power ANT protocol to scan for nearby devices. This allows us to detect devices in close proximity at a lower power budget and much faster, usually in less than $600\,\mathrm{ms}$ compared to $30\,\mathrm{s}$ of a typical Bluetooth scan. This increased time resolution by a factor of up to 50 enables us to measure how groups of firefighters split and merge during a mission.

Each smartphone constantly transmits a unique ID and searches in parallel for devices contained in a search list. Every five seconds, we determine which of the devices was seen by each other device and cluster this proximity data to detect groups of firefighters that are in close proximity. The clustering is done by grouping all pairs of devices together that are connected by at least one link. A temporal filter is then applied to smooth the clustering result. To also consider whether two firefighters are on the same floor level, the measured difference in atmospheric pressure is taken into consideration. In case that the absolute pressure difference is more than $1\,\mathrm{hPa}$, which corresponds to about $8\,\mathrm{m}$ to $10\,\mathrm{m}$ in height difference, we conclude that two firefighters are on different levels and thus are not close to each other. A more detailed description and evaluation of our group proximity sensing method can be found in [13].

[2] `http://www.tornadoweb.org`
[3] `http://www.mongodb.org`
[4] `http://d3js.org`
[5] `http://code.shutterstock.com/rickshaw`

### Performance Metrics

From the smartphone sensor data, we extract the following temporal and behavioral performance metrics. In general the behavioral performance metrics are calculated for each firefighter over a defined period of time such as a mission phase or the complete mission. Additionally, to address the timing aspect of team performance and to visualize how a mission evolves over time, we calculate the behavioral metrics on consecutive periods of 30 seconds.

*Behavioral Performance Metrics*

**Movement Activity** To detect body movement activity, first the sliding standard deviation of the acceleration magnitude $\sigma_a$ over one second is calculated and then a threshold based approach is used to segment the motion data into active and non-active segments. The movement activity describes how much of a period a firefighter was active and is given by

$$\text{movement activity} = \frac{1}{N}\sum_{n=1}^{N}[\sigma_a(n) > \tau_a], \tag{1}$$

with $\tau_a$ being an activity threshold and $[.]$ being the indicator function. The activity threshold $\tau_a$ was learned from the movement data using a two component Gaussian Mixture Model.

**Movement Intensity** is given by the median of the absolute linear acceleration magnitude. Linear acceleration is calculated by subtraction of the median value from the acceleration magnitude.

**Movement Variability** is given by the inter-quartile-range of the absolute linear acceleration magnitude.

**Speech Activity** To automatically detect speech from the recorded raw audio data, we use the long-term-spectral-variability (LTSV) measure presented in [16]. In our previous work [14], we have shown that LTSV can detect speech activity with high accuracy even in noisy firefighting scenarios. Analogous to movement activity, speech activity describes how much of the mission time a firefighter or someone near him spoke.

*Temporal Performance Metrics*

**First Above Ground** In missions which require the turntable ladder to be used, the time that a firefighter is first above ground level is calculated using the atmospheric pressure signal. Using the pressure signal of the engineer who operates the firetruck on ground level as the reference signal, we calculate the difference in atmospheric pressure measured at each firefighter and the engineer. In case that the pressure difference is more than $1\,\mathrm{hPa}$, which equals to roughly $8\,\mathrm{m}$ in height difference, the time that a firefighter is first above ground level is calculated.

**Arrival On-Site** For real-world incidents, the time of arrival on-site is given by the length of the *approach* phase.

## VALIDATION OF PERFORMANCE METRICS

In order to validate the proposed performance metrics, we have monitored 16 firefighting teams during a training scenario in a fire simulation building. Based on the performance metrics, we compare the teams and show how the metrics relate to the mission completion time, one important measure of performance.

### Data Collection during Trainings

The data collection took place on the training facilities for first responders in a major city of Switzerland. We staged our experiments in the fire simulation building where a variety of training scenarios can be realistically simulated. During trainings, which range from kitchen fires to burning cars in the garage, firefighters are confronted with real fires, extreme heat, high humidity, severely restricted visibility and thick smoke.

Together with the training instructors, we designed a non-standard training scenario with increased difficulty to ensure that different teams would not perform equally well. In the chosen training scenario a fire on the third floor of an apartment building is reported by an automatic fire alarm system and the fire department sends a squad consisting of a fire truck and a turntable ladder. The squad includes eight to nine firefighters, split into three firefighters on the turntable ladder and five to six firefighters on the fire truck.

Each firefighter has a specific role which is fixed to the seating position in the firetrucks. The incident commander (IC) is in charge and keeps track of the ongoing operation. On-site, the driver of the turntable ladder (L) is responsible of operating the ladder, whereas the driver of the fire truck becomes the engineer (E) who operates the water pumps. The engineer is also is responsible to keep track of which firefighter uses the self contained breathing apparatus (SCBA) for how long. All other firefighters are part of a troop and thus potentially use the SCBA. First and second troop are composed of a troop leader (T1a, T2a) and one or two other firefighters (T1b, T1c, T2b, T2c).

As soon as the squad arrives at the scene the incident commander analyses the scene and decides how to position the fire trucks, which hose to use, the size of the first troop and where to enter the building. After the decision is made, the incident commander gives orders to his squad and the preparation to enter the building via the turntable ladder begins. As soon as the hose is prepared and the troop is ready, the turntable ladder brings the troop upwards to the roof window where the troop members enter the building.

When the first firefighters enter the building, it is already filled with thick smoke so that the troop has to navigate blindly to the fire which is located one floor below the level of the roof window at a staircase of a maisonette apartment. On the way towards the fire, an unexpected dummy person has to be found and rescued. At this point the troop leader has to decide how to correspond to the new situation as he did not know in advance that a person was at risk. Only after the dummy person is safe the fire should be extinguished, which can either be done by the first troop or by a second troop.

**Figure 2. Impressions of training scenario. Firefighters had to enter through a roof window and navigate in low-visibility to a fire on the third floor, rescue a unexpected dummy person and extinguish the fire.**

We successfully recorded 16 training runs of the same scenario. All training runs were videotaped. We used two regular cameras to record outside and a thermographic camera to record inside the building. Impressions of the scenario are presented in Figure 2. In all runs, the location of entrance was fixed to be the roof window. We chose a single point of entrance for two reasons: First, it made runs more comparable as it reduced variability between runs and second, it increased the difficulty as firefighters had to fight against the heat of the fire maneuvering from upper to lower floors.

In total 51 male professional firefighters, aged $35 \pm 10$, took part in the data collection. The data recording was scheduled on four consecutive days. In order to have many different team compositions, the firefighters of the morning and afternoon sessions were exchanged completely and in each run of one session the roles of the firefighters were changed in such a way that at least the troop was always composed of different firefighters. The incident commander within one session stayed always the same.

For later analysis, we used the video recordings to manually split the training scenario into two phases. In the *preparation* phase, the turntable ladder is positioned, the hose is prepared and the troop uses the turntable ladder to reach the roof window. We defined the *preparation* phase to start when the first truck reached it's final position and to last until the turntable ladder reached was positioned. The *execution* phase lasted until the troop reported to the incident commander that the fire had been extinguished.

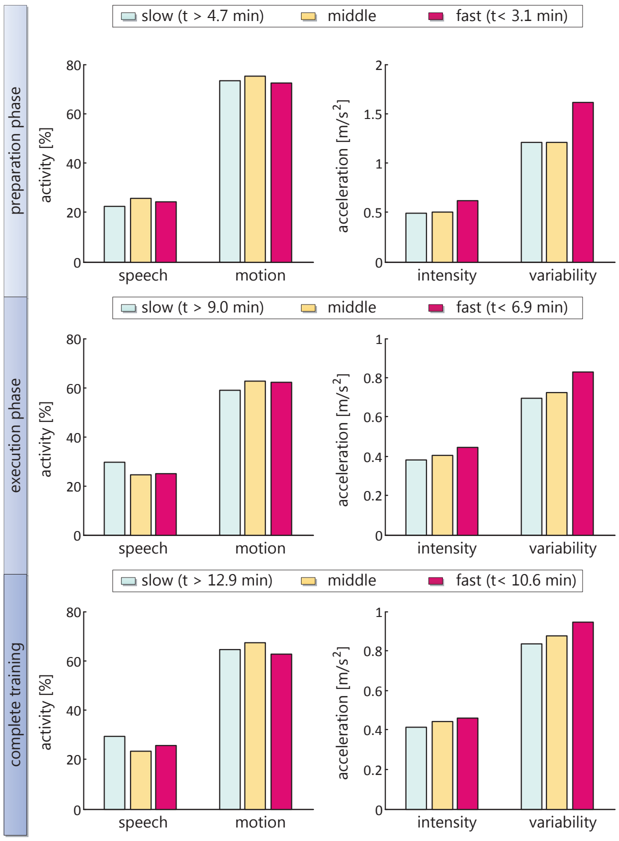


**Figure 3. Performance metrics during preparation and execution phase, as well as for the complete training. For each phase teams were split into slower, middle and faster teams by the first and third quartiles of the respective phase durations (respective times are given in brackets).**

| | duration of | | |
|---|---|---|---|
| | preparation | execution | complete |
| movement activity | $-0.03$ | $0.01$ | $0.03$ |
| movement intensity | $-0.55^{*}$ | $-0.34$ | $-0.32$ |
| movement variability | $-0.55^{*}$ | $-0.33$ | $-0.25$ |
| speech activity | $0.06$ | $0.57^{*}$ | $0.39$ |
| first above ground | $0.87^{**}$ | $-0.10$ | $0.41$ |

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$

**Table 1. Correlations between performance metrics and duration of preparation and execution phase as well as for the complete training duration.**

### Analysis of Performance Metrics

In the following, we will investigate how the performance metrics are related to mission completion time, one of the most critical indicators of team performance in firefighting. We compare 16 teams in terms of their averaged performance metrics over all involved firefighters. In Figure 3 the mean values of the performance metrics observed by slow, middle and fast teams are shown for the *preparation* and *execution* phase, as well as for the *complete* training mission.

The categorisation into slow, middle and fast teams was done in each phase separately by the quartiles of the phase completion time. The completion times of the slow teams are consequently in the highest quartile, whereas the completion times of the fast teams are in the lowest quartile. In addition to the bar plots, the linear correlation coefficients between the performance metrics and the phase duration times are given in Table 1.

As can be seen in the top of Figure 3, all teams in the *preparation* phase were active for about 70 % of the phase, however faster teams showed higher *movement intensity* and *movement variability*. This relationship is also seen by the negative linear correlation between the movement related metrics and phase duration. The more average movement intensity and variability across firefighters the shorter the *preparation* phase. Interestingly, *speech activity* is not correlated with the duration of the *preparation* phase. Most possibly this stems from the fact, that the preparation phase of the chosen training scenario is standard procedure and thus known by heart so that no extra coordination is required. The performance metric *first above ground* is a good indicator of the length of the preparation phase ($R = 0.87$); the two measures are not perfectly correlated because troops needed more or less time to enter the roof window.

As in the *preparation* phase, faster teams also showed higher *movement intensity* and *movement variability* during the *execution* phase. Again this can be seen in the negative correlations between *movement intensity*, *movement variability* and the *execution* phase duration. During the *execution* phase, slower teams showed more *speech activity* than faster teams. Thus, we can observe a positive correlation between *speech activity* and *execution* phase duration. The higher amount of communication might indicate more need for explicit coordination which consequently leads to longer *execution* phases.

Analysing the complete training duration, we find that overall slower teams tend to speak more, as seen by the positive correlation between *speech activity* and training duration. Slower teams showed less *movement intensity* and *movement variability*, while beeing active for the same amount.

The analysis of the performance metrics showed that the metrics are valid performance indicators as they are not only correlated with the temporal performance measures of phase and training duration, but also provide more insight why teams might have been faster than others.

## COENOFIRE IN THE WILD

In the following, we describe the conducted real-world study with professional firefighters. We detail the data collection procedure during real-world deployment, analyse mission operations of a real-world fire incident and show how the smartphone data can support post mission feedback.

### Data Collection

Over a period of six weeks, we monitored a squad of nine professional firefighters in 33 shifts during real-world incidents. Each squad itself was composed out of a turntable ladder with three firefighters and a fire truck with five to six firefighters varying with the station's work plan.

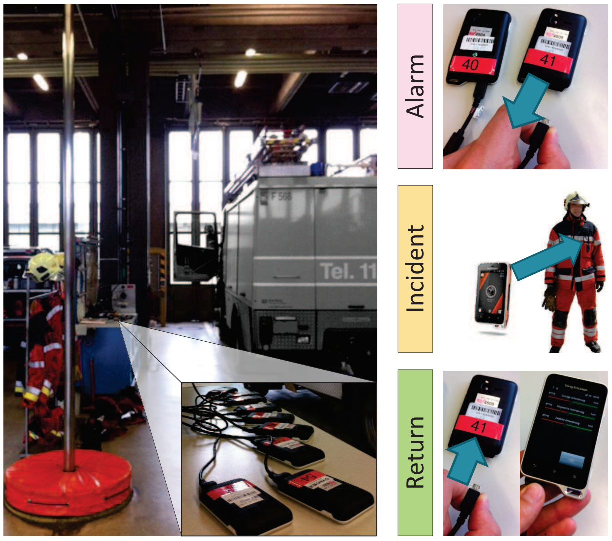


**Figure 4. Deployment of smartphones during the data collection phase. Smartphones were placed and charged next to the fire truck to be picked up by the firefighters before leaving the fire station.**

Work is organized in three 24 hours shifts meaning that a firefighter is on duty for 24 hours and off for the next 48 hours. Each shift begins in the morning at 7 am with a report of the previous shift and ends with a handover to the next shift the next morning. During a shift firefighters maintain equipment, take part in special training and keep themselves fit with sports. In case of an incident alarm, the firefighters stop their everyday activities, put on their protective clothing and jump on the fire trucks to drive to the incident location.

Having the requirements of an in-work-place recording in mind (see 'Requirements on Monitoring System'), we integrated the data collection procedure into the daily routine of the fire brigade as follows: The smartphones were placed on a sideboard located left to the fire truck and were attached to a powered USB Hub which served as charging station (see Figure 4). In this way, the phones were always charged and ready to be used. As soon as an alarm occurred, the firefighters un-plugged the smartphone labeled with the number of their daily position and put it inside the left inside pocket of their jacket. Un-plugging the smartphone from the charging cable triggered the recording app to automatically start the data collection. In this way the firefighters were not further disturbed from their normal routine. When the firefighters returned to the station, they reconnected the smartphone to the charging cable which triggered the app to display a short post mission questionnaire including 10 questions.

During the data collection period the monitored squads were involved in 76 incidents of which 43 were triggered by automatic fire alarm systems, 9 were real fire incidents and the rest were other incident types such as a burning garbage container, a trapped person in an elevator or water inside a building. In total 71 firefighters participated in the real-world data collection.

### A Real-World Mission

In the following, we visualize the first 30 minutes of smartphone data recorded during a fire at a multi-family residential home. We choose to show this mission, because a detailed mission report was available. Impressions of the fire incident are presented in the top of Figure 5.

When leaving the fire station, only a street intersection for the incident location was provided and the detailed address of the incident was unclear. When the squad arrived at the incident scene the police informed the incident commander that two persons were still missing in the apartment on the third floor. Consequently, the first concern of the incident commander was to rescue the missing persons and he ordered the first troop to search and rescue the persons via the staircase using the quick-attack hose. Afterwards, the incident commander ordered the second troop to attack the fire at the balcony via the turntable ladder in order to extinguish the fire and to save the roof soffit. The incident commander then ordered a second squad for backup. The persons were found and rescued by the first troop and other four persons were evacuated via a side balcony on the fourth floor. The whole mission lasted for more than three hours.

### Data Supported Mission Feedback

In Figure 5 the smartphone data illustrates how the firefighting operations evolved over time. Presented are, from top to bottom, atmospheric pressure, groups of firefighters who are in proximity to each other, motion intensity and speech activity. The mission phases are underlayed in different colors, the *approach* phase in light blue, the *on-site* phase in light orange.

From the pressure signal, we can infer altitude changes while approaching the incident site and relative differences in altitude between firefighters during the *on-site* phase, indicating when a troop operated above ground level. The proximity graph displays, in form of a narrative chart, which firefighters were in proximity during each point in time of the mission. Each firefighter is represented by a line of different color and lines that are close to each other represent a group of firefighters that are in proximity. The graph also indicates on which level relative to the ground level a group of firefighters operates. The movement intensity of the firefighters is aggregated each 30 seconds and is illustrated in form of a stacked bar chart, which allows to infer when the squad was most active and who of the firefighters was most active. Analogous, speech activity detected at each firefighter is displayed. The values are normalised and 100 % would represent that speech was detected at all firefighters for the entire 30 seconds period.

Looking at the *approach* phase first, we notice a short peak in *movement intensity* (see 1c) and a merging of all firefighters (see 1b). This is the result of the uncertain incident location and due to the fact that the given street intersection exists twice as one of the streets has circular shape. Consequently, the squad stopped at the first intersection only to find out that they had to continue driving to reach the second intersection where the incident was located.

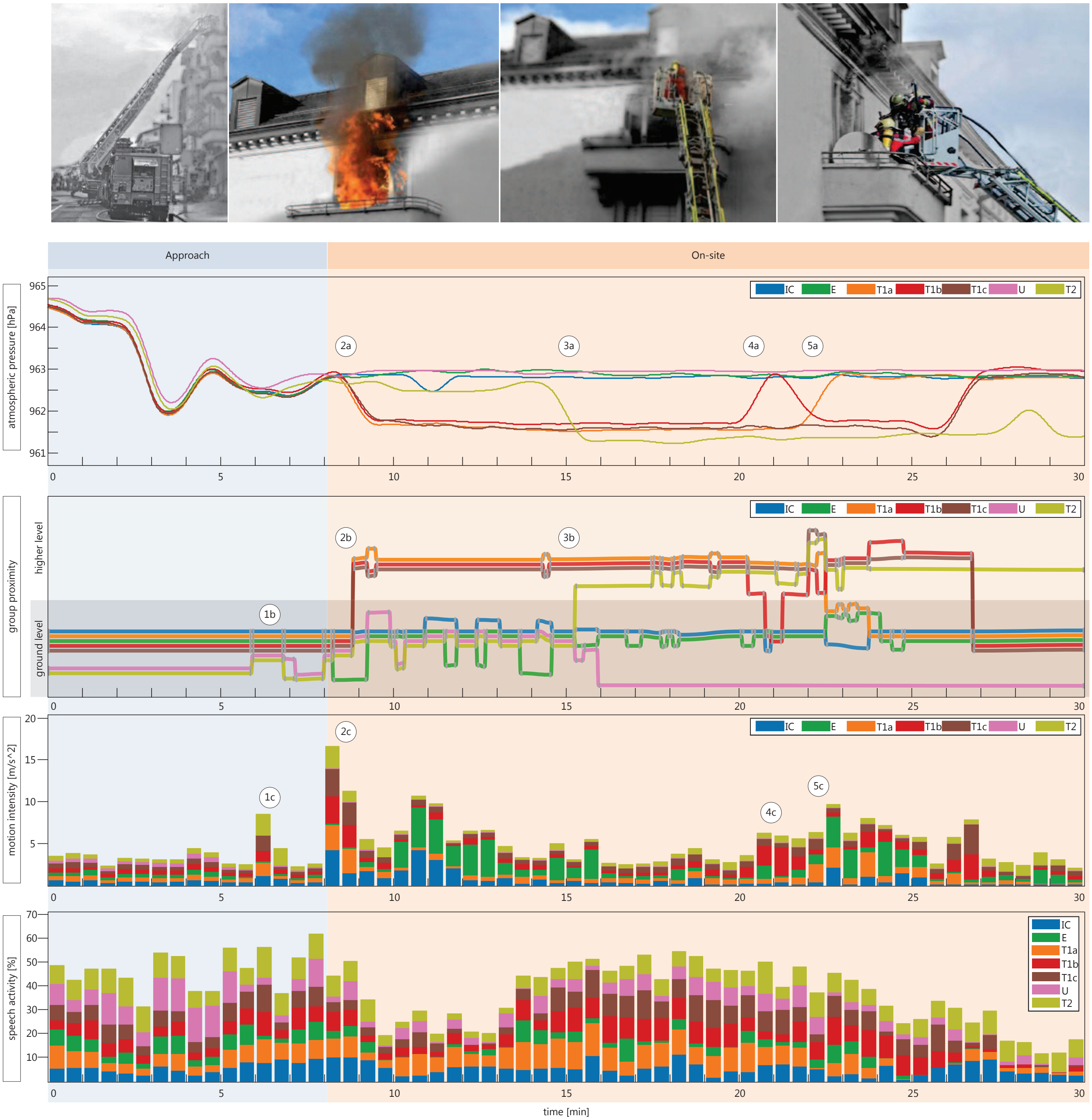


**Figure 5. Impressions and visualisation of the smartphone data recorded during the first 30 minutes of a real-world firefighting mission in a multi-family residential home. Mission time starts as soon as firefighters leave the station. Shown are from top to bottom atmospheric pressure, group proximity, movement intensity and speech activity. Just the pressure signals alone indicate when first (2a) and second troop (3a) reached higher floors and when two missing persons were rescued (4a, 5a).**

The high peak of *movement intensity* at the beginning of the *on-site* phase (see 2c) indicates the rapid start of all firefighters, especially of the first troop which had to rescue the missing persons. Already within one minute after arrival on-site, the first troop is at least 8 meters above the engineer, which can be seen from the pressure signals (see 2a) and the group clustering (see 2b). Together with the high motion intensity this shows the fast operation of the first troop.

Between minutes 10 and 14 of the mission, the engineer E and the incident commander IC moved intensively, while at the same time the speech activity of all firefighters dropped considerably. In this period of the mission, automatisms were at play and all firefighters followed their role specific tasks indicating that everything went as supposed to. For the engineer E this meant to connect the fire truck to the next fire hydrant, while the incident commander overviewed the situation on-site.

At minute 15 of the mission, the second troop arrived at the balcony to extinguish the fire at the roof which can be seen from the pressure signal (see 3a) and the proximity clustering and (see 3b). It appears, that only one firefighter was involved in this task, however this is not true. Because we monitored only one squad, not all firefighters involved in the mission carried a smartphone.

Twelve minutes after arriving *on-site*, the first person was found and rescued by troop member T1b (see 4a,4c). From the fourth floor, T1b carried the person down the staircase to the first responders waiting outside the building. Little later, the second person was rescued and carried down by troop leader T1a (see 5a,5c).

### Data Completeness

In the following, we analyze data completeness and evaluate how well the data collection procedure could be integrated into the daily routine of the firefighters. We first look at how well the charging procedure worked during deployment. In the top left of Figure 6 the overall data completeness is shown. It can be seen that the smartphones were on and ready to record in 93 % of the expected recordings, where the number of expected recordings is given by the product of the number of missions and the number of firefighters involved. In total, we collected 236 recordings.

To better understand when firefighters did not take the smartphone with them, we looked at the following factors which might have had an influence on the data collection. All factors are illustrated in Figure 6.

**Period of Data Collection** We have noticed that the data completeness rate decreased over the period of the data collection. Within the first two weeks 62 % of all expected recordings were completed. The completeness rate dropped in the second fortnight to 42 % and reached 28 % in the last two weeks. The low data completeness towards the end of the data collection is probably because this period fell into a holiday season and the fact that firefighters thought that the data collection had ended.

**Incident Time** We observed a higher than average data completeness for incidents that occurred in the afternoon and the lowest for incidents at night. At night and at the first incident of the day firefighters forgot to pick up the smartphones more often.

**Incident Type** Dependent on the incident type the data completeness rate varies from 36 % to 69 %, with one clear exception: In case of an aircraft incident almost no data was recorded. Because firefighters have to be at the airplane within three minutes, time is extremely rare and the firefighters could not spent any additional time un-plugging the smart phone.

**Fire Truck** We noticed that firefighters of the fire truck remembered the phone almost twice as often compared to firefighters of the turntable ladder. Most likely this is due to the fact, that all smartphones were located close to the fire truck, but further away from the turntable ladder.

**Workgroup** Comparing the three shift workgroups, we observed that the first workgroup had a data completeness rate of 49 %, whereas the two other groups had 36 % and 34 % completeness rate, respectively. It appears that the first workgroup was highly motivated to participate in the data collection.

## DISCUSSION AND CONCLUSION

We have presented CoenoFire, a smartphone based sensing system for monitoring performance indicators of firefighting missions. We successfully deployed CoenoFire in a professional fire brigade over a period of six weeks in which 71 firefighters used the system in 76 real-world missions.

The performance of firefighters depends on many factors, and any metric derived from smartphone data can only give indications of what might have been good or bad during a training or mission. However, we have demonstrated, that with only the smartphone in the jacket of the firefighters, detailed information can be extracted that is valuable for incident commanders and training instructors. In the recorded training scenario, we have seen that longer mission durations are correlated with more speech activity of the squad which could indicate that more explicit coordination was needed. Also, we found that shorter preparation and execution phases were related to higher movement intensity and variability.

We have seen that in scenarios which spread across different floors, already the signal of a pressure sensor can provide information about when the first troop reached a level above or below the reference level of the engineer, who is in that troop, and for how long the troop was operating. Combined with proximity information derived from low-power communication radios, we showed how groups merge and split during missions to perform different tasks. We showed, how the smartphone data can be visualised to show temporal evolvement and how important mission phases and events can be detected. As the training instructor of the fire brigade put it: "I can really see how the mission evolved, it is a great tool for post-incident feedback and training".

From the results of the data completion analysis and personal feedback from the firefighters, we conclude that overall the acceptance of the smartphone to recording data during missions was high, but that the already simple data collection procedure has to be further improved. This could be achieved for example by integrating the smartphone better into the jacket to reduce the user effort.

In future work, the audio data could be mined for reoccurring ambient sounds which could further improve the logging of important events throughout missions.

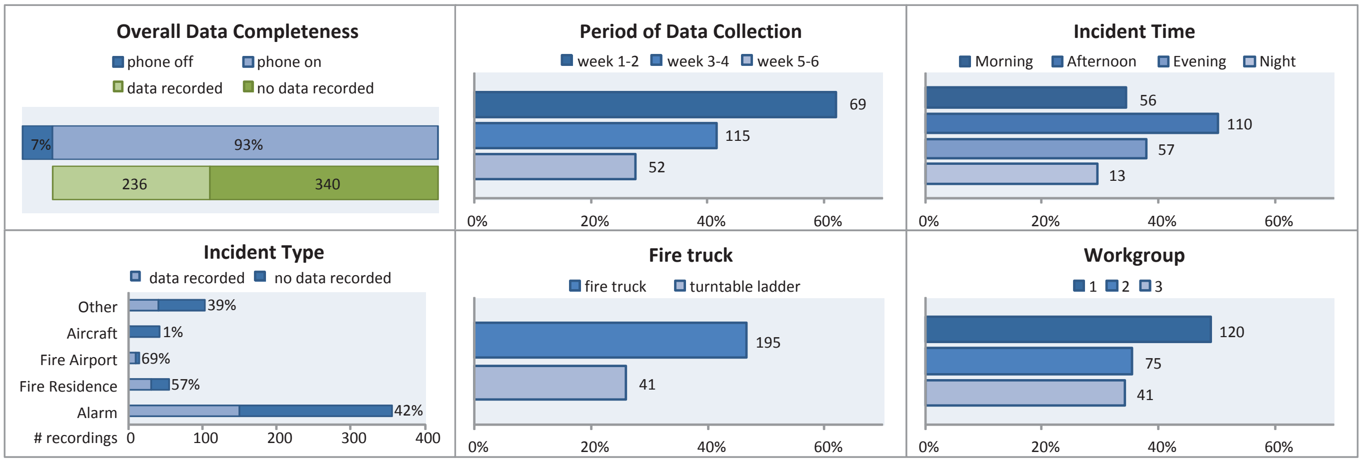


**Figure 6. Overall data completeness and factors which influenced data completeness during real-world deployment. The system was on and ready most of the time and firefighters carried the smartphone during incidents in more than one third of all possible incidents. Given are absolute values for the number of recordings and percentage values indicate the fraction of actual recordings given the number of expected recordings.**

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